ARTIFICIAL IMMUNE SYSTEM AND PARTICLE SWARM OPTIMIZATION FOR ELECTROENCEPHALOGRAM BASED EPILEPTIC SEIZURE CLASSIFICATION

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To my beloved family

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ABSTRACT

Automated analysis of brain activity from electroencephalogram (EEG) has indispensable applications in many fields such as epilepsy research. This research has studied the abilities of negative selection and clonal selection in artificial immune system (AIS) and particle swarm optimization (PSO) to produce different reliable and efficient methods for EEG-based epileptic seizure recognition which have not yet been explored. Initially, an optimization-based classification model was proposed to describe an individual use of clonal selection and PSO to build nearest centroid classifier for EEG signals. Next, two hybrid optimization-based negative selection models were developed to investigate the integration of the AIS-based techniques and negative selection with PSO from the perspective of classification and detection. In these models, a set of detectors was created by negative selection as self-tolerant and their quality was improved towards non-self using clonal selection or PSO. The models included a mechanism to maintain the diversity and generality among the detectors. The detectors were produced in the classification model for each class, while the detection model generated the detectors only for the abnormal class. These hybrid models differ from each other in hybridization configuration, solution representation and objective function. The three proposed models were abstracted into innovative methods by applying clonal selection and PSO for optimization, namely clonal selection classification algorithm (CSCA), particle swarm classification algorithm (PSCA), clonal negative selection classification algorithm (CNSCA), swarm negative selection classification algorithm (SNSCA), clonal negative selection detection algorithm (CNSDA) and swarm negative selection detection algorithm (SNSDA). These methods were evaluated on EEG data using common measures in medical diagnosis. The findings demonstrated that the methods can efficiently achieve a reliable recognition of epileptic activity in EEG signals. Although CNSCA gave the best performance, CNSDA and SNSDA are preferred due to their efficiency in time and space. A comparison with other methods in the literature showed the competitiveness of the proposed methods.

ABSTRAK

Analisis automatik aktiviti otak daripada elektroensefalogram (EEG) mempunyai aplikasi yang ketara dalam pelbagai bidang seperti penyelidikan epilepsi. Kajian ini telah mengkaji keupayaan pilihan negatif dan pilihan klonal dalam sistem imun tiruan (AIS) dan pengoptimuman kumpulan zarah (PSO) untuk menghasilkan pelbagai kaedah yang boleh dipercayai dan cekap untuk pengecaman serangan epilepsi berdasarkan EEG dimana ia masih belum diterokai. Pada awalnya, model pengelasan berasaskan pengoptimuman telah dicadangkan untuk menggambarkan penggunaan secara tunggal bagi pilihan klonal dan PSO untuk membina pengelas terpusat terhampir bagi isyarat EEG. Setelah itu, dua model hibrid bersandarkan pengoptimuman pilihan negatif telah dibangunkan untuk mengkaji gabungan teknik berdasarkan AIS dan pilihan negatif dengan PSO dari perspektif pengelasan dan pengesanan. Dalam model ini, satu set pengesan telah dicipta menggunakan pilihan negatif sebagai toleran-kendiri dan kualiti kedua-duanya bertambah baik terhadap tak kendiri menggunakan pilihan klonal atau PSO. Model-model ini mengandungi mekanisma untuk mengekalkan kepelbagaian dan pengitlakan dalam kalangan pengesan. Pengesan telah dihasilkan dalam model pengelasan bagi setiap kelas, manakala model pengesanan menjana pengesan hanya untuk kelas tidak normal. Model-model hibrid ini berbeza antara satu sama lain dalam konfigurasi penghibridan, perwakilan penyelesaian dan fungsi objektif. Ketiga-tiga model cadangan disarikan kepada beberapa kaedah inovatif dengan mengaplikasikan pilihan klonal dan PSO untuk pengoptimuman, iaitu algoritma pengelasan pilihan klonal (CSCA), algoritma pengelasan zarah kumpulan (PSCA), algoritma pengelasan pilihan klonal negatif (CNSCA), algoritma pengelasan pilihan kumpulan negatif (SNSCA), algoritma pengesanan pilihan klonal negatif (CNSDA) dan algoritma pengesanan pilihan kumpulan negatif (SNSDA). Kaedah-kaedah ini telah dinilai ke atas data EEG menggunakan pengukuran lazim dalam diagnosis perubatan. Hasil kajian menunjukkan bahawa kaedah cadangan telah mencapai pengecaman yang cekap dan boleh dipercayai bagi aktiviti epileptik dalam isyarat EEG. Walaupun CNSCA memberikan pencapaian yang terbaik, namun CNSDA dan SNSDA menjadi pilihan kerana kecekapan mereka dari aspek masa dan ruang. Perbandingan dengan kaedah-kaedah lain dalam literatur menunjukkan kebolehsaingan pada kaedah yang dicadangkan.

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LIST OF ABBREVIATIONS

AIS	-	Artificial Immune System
ALC	-	Artificial Lymphocyte
BCA	-	B-Cell Algorithm
CCR	-	Correct Classification Rate
CNSCA	-	Clonal Negative Selection Classification Algorithm
CNSDA	-	Clonal Negative Selection Detection Algorithm
CSAs	-	Clonal Selection Algorithms
CSCA	-	Clonal Selection Classification Algorithm
CV	-	Cross Validation
DWT	-	Discrete Wavelet Transform
EEG	-	Electroencephalogram
EEGs	-	EEG Signals
HOV	-	Hold-Out Validation
NCC	-	Nearest Centroid Classifier
NIS	-	Natural Immune System
NSA	-	Negative Selection Algorithm
PSCA	-	Particle Swarm Classification Algorithm
PSO	-	Particle Swarm Optimization
SNSCA	-	Swarm Negative Selection Classification Algorithm
SNSDA	-	Swarm Negative Selection Detection Algorithm
TNR	-	True Negative Rate
TPR	-	True Positive Rate
WT	-	Wavelet Transform

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CHAPTER 1

INTRODUCTION

1.1 Introduction

The human brain is a highly complex organ representing the center of the nervous system. It contains about 100 billion of interconnected neurons. A neuron is a cell that uses biochemical reactions to receive, process, and transmit information and commands (Aziz, 2007; Rabbi, 2013).

Activity of brain describes a wide range of different states which are normal and abnormal. Normal states consist of physical states such as sleep, wakefulness, and exertion; as well as mental states such as calmness, happiness, and anger. Abnormal states are primarily noted in neurological disorders such as schizophrenia, insomnia, and epilepsy (Ghosh Dastidar, 2007; Polat and Güneş, 2008). However, there is significant overlap in the activation patterns of brain states. Therefore, it is very difficult to use these patterns to conclusively identify the state.

The techniques that are used to measure the activities of the brain can be broadly classified into two categories: hemodynamic/metabolic and electromagnetic (Scanziani and Häusser, 2009). The functional neuroimaging techniques based on principles of hemodynamic such as Functional Magnetic Resonance Imaging (fMRI) or metabolic such as Positron Emission Tomography (PET) infer functional activity through measuring local changes in blood oxygenation levels or glucose metabolism respectively (Ermer, 2001). Conversely, electromagnetic techniques describe electrical properties of biological cells and tissues. Magnetoencephalogram (MEG) and electroencephalogram (EEG) are the electromagnetic techniques widely employed to measure the electrical activities of neurons from the magnetic fields and the fluctuations in potential respectively (Ermer, 2001; Rabbi, 2013).

Among these techniques, EEG is favorable due to several advantages: the electrical activity of the brain is recorded directly, it is less cumbersome and very inexpensive, and its high temporal resolutions (milliseconds, mS) which allow direct observation of the dynamic brain activity. With EEG, it is possible to follow the rapid changes in cortical activity that reflect neural processing functions, where the electrical events of single neurons typically last from one to several tens of mS (Ermer, 2001; Majumdar, 2011; Stam *et al.*, 1999; Wong, 2004).

The EEG records electric potentials that are generated by neurons in the brain. The brain activity in different areas over a time period is measured, using many electrodes in order to characterize the spatio-temporal dynamics of neuronal activity in the brain. This result in multi-channel EEG signals, each represents an EEG signal at different positions (Ghosh Dastidar, 2007; Madan, 2005). The EEG can be a non-invasive or invasive with respect to electrode location. In non-invasive technique, the EEG signals are recorded from the surface of the head based on the International 10-20 system (Homan *et al.*, 1987; Jasper, 1958; Shibasaki, 2008). The EEG in this case is referred to as the scalp EEG. The invasive electrodes consist of three types: electrocorticogram (ECoG), intracranial EEG (IEEG), and depth EEG. The ECoG is measured from the cortex directly using subdural electrodes strip/grid; whereas the IEEG is measured from inside the skull; and finally the depth EEG is measured from inside the brain (Gardner, 2004).

The EEG signals (EEGs) conveys valuable information about the states of the brain. Therefore, EEGs analysis has important applications in brain computer interface (BCI), psychotropic drug research, monitoring patients in critical condition in the ICUs, sleep studies, and epilepsy research (Majumdar, 2011).

Epilepsy is characterized by recurrent seizures due to temporary electrical disturbance of the brain (Acharya *et al.*, 2012b). The occurrence of a seizure seems unpredictable and its course of action is still largely unknown to date. Research is therefore needed to gain a better understanding of the mechanisms generating epileptic seizures. Careful analysis of EEGs could provide valuable insight into this widespread brain disorder (Adeli *et al.*, 2003; Subasi, 2007).

Monitoring of epilepsy requires a continuous EEG recording for durations extending usually days. The recorded data is intensively used to study the epileptic seizures for pre-surgical evaluation. It provides essential information for locating the brain regions that generate epileptic activity (Jordan, 1993; Ocak, 2008). In some cases, epilepsy patients have seizures that are uncontrollable. Recently, methods have started being developed to treat medically resistant epilepsy. In those methods, implantable medical devices monitor the electrical activities of the brain and deliver a local therapy; such as chemical infusions or electrical stimulation; to the affected regions of the brain in order to reduce the frequency of seizures (Alam and Bhuiyan, 2013; Patnaik and Manyam, 2008; Tang and Durand, 2012).

1.2 Problem Background

Epileptic activity is typically studied using continuous long-term EEG monitoring systems. As a result, large amounts of EEGs are recorded (Madan, 2005). Nature of the signals is dynamic with high temporal resolutions (Majumdar, 2011). Visual analysis of the EEG recordings by a reviewer is clearly a very time consuming and costly task. Moreover, the analysis depends on expertise and experience of the reviewer, and therefore it is subjective (Alam and Bhuiyan, 2013). These challenges are further augmented in cases of the scalp EEGs where the number of channels is increased to more than 300 channels (Liu *et al.*, 2012; Oostenveld and Praamstra, 2001) and overlapping symptomatology epileptic seizures with other neurological disorders (Song and Zhang, 2013). Hence, automating the process of epileptic seizures recognition in EEGs is of great importance. The development in studies of signal processing and data mining has provided a great possibility to manipulate this problem through identifying associations or hidden patterns in EEGs (Song and Zhang, 2013).

Although there are a large amount of information in EEGs, but some contents of EEG are not useful. Lower frequency oscillations are characterized as artifacts, and include electrocardiograms, eye blinks, and muscle movements, to name a few. On the other hand, very high frequency oscillations may be recorded due to electromagnetic interference. All these contents of EEGs can be categorized as noises and need to be removed (Ghosh Dastidar, 2007; Song and Zhang, 2013). Therefore, various techniques of signal processing theory have been employed to extract the features of relevant information in EEGs. These techniques include the Fast Fourier transform (FFT) (Polat and Güneş, 2007; Polat and Güneş, 2008; Tezel and özbay, 2009), autoregressive (AR) (Alkan *et al.*, 2005; Übeyli, 2010), and wavelet transform (WT) (Orhan *et al.*, 2011; Song and Zhang, 2013; Subasi, 2007; Übeyli, 2009c).

Signal processing based on FFT retains only the frequencies information whereas the information of the time is lost (Amirmazlaghani and Amindavar, 2009). Furthermore, the FFT suffers from large noise sensitivity (Subasi, 2005b). The short-time Fourier transform can localise information of frequency and time using a uniform time window. Therefore, it has limited precision where all frequencies have constant resolution (Xu *et al.*, 2009). AR method reduces the problem of spectral loss and provides better resolution of frequency, but it is good only for stationary signals. Since the EEGs are non-stationary, the AR is not suitable to analyze frequency of such signals (Subasi, 2005a). In contrast, the WT has ability for localizing frequency and time components of signal with a variable window size that is adapted based on the frequency. Hence, the WT has become an efficient method for feature extraction of non-stationary signals (Ocak, 2009). In this work, EEG dataset used in the current study has been analyzed using WT for feature extraction.

Feature extraction is the preliminary stage in which highly informative measures are produced as representative features for EEGs. The main stage of an automated system for epileptic seizures recognition in EEGs is EEG patterns classification. In this stage, the machine learns to mine the EEGs to differentiate between EEG patterns in epileptic state and other brain states in order to make rational decisions on the classes of the patterns (Li, 2010; Majumdar, 2011). Thus, applications of machine learning techniques in analyzing EEGs have an increasing interest in recent years. In biomedical research, it is essential to understand and develop advanced signal classification techniques for the recognition of EEG changes (Siuly *et al.*, 2011). In this regard, soft computing is the most promising approaches among many techniques of machine learning. The soft computing strives to achieve robust and practical solutions at reasonable cost by tolerating uncertainty, imprecision and approximation to be part of the computational model (Goel *et al.*, 2013; Majumdar, 2011).

In this context, tremendous efforts have long been made by researchers trying to solve the problem of automatic diagnosis of epilepsy from EEGs, and thus several methods have been presented in the literature. Many of these approaches include techniques that belong to the area of soft computing such as different types of artificial neural networks (ANN) (Kumar *et al.*, 2010; Orhan *et al.*, 2011; Song and Zhang, 2013; Subasi, 2007; Übeyli, 2008b; Übeyli, 2009c), adaptive neuro-fuzzy inference system (ANFIS) (Güler and Übeyli, 2005; Kannathal *et al.*, 2005; Übeyli, 2009b), support vector machine (SVM) (Chandaka *et al.*, 2009; Joshi *et al.*, 2014; Nicolaou and Georgiou, 2012; Subasi and Gursoy, 2010; Übeyli, 2008a), and artificial immune system (AIS) (Polat and Güneş, 2008).

Artificial immune system (AIS) emerged in the 1990s as a flourishing field of soft computing (de Castro and Timmis, 2002b; de Castro and Timmis, 2003; Gao *et al.*, 2009b). The AIS can exhibit robust and powerful capabilities in information processing to solve complex problems. From the perspective of computational, it has important characteristics such as maintenance, diversity, learning, and memory. Moreover, the AIS shows fast convergence speed with ability to avoid the immaturity and degeneration of the searching (Aydin *et al.*, 2010; Guo, Lei *et al.*, 2011; Leung *et al.*, 2007). To date, research primarily has focused on three main components within AIS which include the theories of negative selection, clonal selection and immune network (Smith and Timmis, 2008).

The algorithms of AIS have not been widely explored in the field of EEG-based diagnosis. Actually, there are very few studies in which AIS models have been employed to recognize epileptic seizures in EEGs. Polat and Güneş (2008) used an algorithm belongs to immune network theory called artificial immune recognition system (AIRS) to propose a system with three stages: feature extraction using FFT, dimensionality reduction based on PCA, and EEG classification using AIRS with fuzzy resource allocation. However, there are also a few studies that have applied AIS methods in other fields related to EEG. Guo, Lei *et al.* (2011) introduced immune algorithm for feature weights and parameters selection of SVM which was used to classify different mental tasks for EEG-based BCI. Artificial immune network (cob-aiNet) was used by Coelho *et al.* (2012) to optimize the feature of EEGs based on Davies-Bouldin index and extreme learning machine ANN classifier for BCI system in motor imagery paradigms.

The negative selection algorithm (NSA) is more appropriate for application in anomaly and fault detection compared to other AIS theories (Amaral, 2011; Aydin *et al.*, 2010). It has been proven to be an efficient algorithm for solving such problems (Garrett, 2005; Ji and Dasgupta, 2007). The NSA was firstly proposed for the real-time detection of computer virus (Forrest *et al.*, 1994). Since then, it has been used widely in such domains as diagnosis of motor fault (Aydin *et al.*, 2008; Gao *et al.*, 2009a; Laurentys *et al.*, 2010; Xinmin *et al.*, 2007), detection of aircraft fault (Dasgupta *et al.*, 2004), and security of communication network (Dasgupta and Gonzalez, 2002; Hoffmeyr and Forrest, 1999). Nevertheless, the NSA has not been investigated in the area of EEGs applications so far.

On the other hand, the random search of the traditional NSA cannot be guaranteed to generate detectors in the most efficient way. That is to say, distribution of the detectors is unbalanced in the problem space. As a result, some regions of abnormal (non-self) space are uncovered, whereas other regions are re-covered by redundant detectors (Aydin *et al.*, 2010; Gao *et al.*, 2007; Wen *et al.*, 2014). Many methods have been introduced in the literature to overcome this drawback (Amaral *et al.*, 2007; Aydin *et al.*, 2008; Aydin *et al.*, 2010; Dasgupta and Gonzalez, 2002; Gao *et al.*, 2006; Gao *et al.*, 2007; Gao *et al.*, 2008; Gao *et al.*, 2009a; Graaff and Engelbrecht, 2006; Igawa and Ohashi, 2009). Most of these methods use optimization techniques, i.e., particle swarm optimization (PSO), genetic algorithm (GA), and clonal selection algorithms (CSAs), to guide the search in NSA and generate detectors with optimal distribution.

Gao *et al.* (2007) used a multi-phase PSO to optimize NSA detectors. It was integrated with anti-collision technique to increase diversity of detectors. However, fixed radius for the detectors is used. A classification algorithm based on NSA has been proposed by Igawa and Ohashi (2009). They applied a clonal selection algorithm named CLONALG in order to generate efficient detectors. In testing stage when a pattern cannot be detected, the radius of each detector is enlarged. However, many detectors in this case may overlap the others and normal (self) space. Aydin *et al.* (2010) proposed a negative selection method using chaotic maps and a CSA. In their algorithm, the chaotic maps are used to initialize the detectors and in mutation operator, whereas the CSA is employed to optimize the coverage and diversity of the detectors. The quality of each detector is evaluated based on the number of data samples recognized by (1) only current detector, (2) current detector and other detectors. The downside is that some parts of problem space may be searched many times. Furthermore, domination of second factor can result in poor coverage and redundant detectors.

Principles of clonal selection have been used to introduce various algorithms that are employed for tasks such as data mining, clustering and optimization. However, clonal selection algorithms (CSAs) are more suitable to deal with optimization problems and have found widespread use in such applications (Aydin *et al.*, 2010; Shojaie and Moradi, 2008). Clonal selection has excellent search abilities with an important mechanism to guarantee diversity of individuals in new generations. Hence, CSAs can avoid the local convergent effectively (Trojanowski and Wierzchoń, 2009; Wang *et al.*, 2008).

In literature, a few studies applied CSAs to solve some optimization or clustering problems in applications of EEGs. Shojaie and Moradi (2008) presented a clonal selection algorithm for features selection and parameters optimization of

SVM. The SVM was used to assess event-related potentials (ERP) in EEGs of guilty knowledge test (GKT) based on the P300 waves. Dursun *et al.* (2012) proposed artificial immune clustering based on clonal selection for data reduction in order to solve class imbalance problem in training data. It was applied for sleep stage classification in EEG, Electrooculogram (EOG), and Electromyogram (EMG) signals using ANN. Their results confirmed superiority of artificial immune method compared to fuzzy C-means clustering. Feature selection also considered using immune clonal algorithm (ICA) to improve detecting epileptic EEGs (Peng and Lu, 2012). It was compared with PSO using four classifiers. The finding showed in general that the ICA slightly outperformed the PSO in classification accuracies.

The clonal selection-inspired algorithms have not been applied previously for EEGs classification. However, the optimization techniques can be employed for classification by representing each class with a centroid (class center) (De Falco *et al.*, 2007; Mohemmed and Zhang, 2008; Omran *et al.*, 2005). The goal is to optimize the positions of all centroids to build nearest centroid classifier (NCC). It is clear that CSAs and PSO can be effectively faced such problem. The PSO is a global optimization algorithm, simple in concept, easy to implement, robust to control parameters and computationally efficient (Eberhart and Shi, 1998; Wang *et al.*, 2007).

To the best of our knowledge, the PSO has not been used for classification of EEGs. However in many works, the classifier of EEGs is trained and/or its parameters are optimized by PSO (Chai *et al.*, 2013 In Press; Cinar and Sahin, 2013; Firpi *et al.*, 2007; Hema *et al.*, 2008; Lin and Hsieh, 2009; Nguyen *et al.*, 2012). Also, it was employed to estimate the locations of sources of electrical activity, e.g. epileptic, in the brain based on the scalp EEGs (Escalona-Vargas *et al.*, 2013; Qiu *et al.*, 2005; Shirvany *et al.*, 2012; Shirvany *et al.*, 2013; Shirvany *et al.*, 2014; Xu *et al.*, 2010). Other EEGs issues have been addressed by PSO such as feature selection (Nakamura *et al.*, 2009; Zhiping *et al.*, 2010) and optimal selection of Electrode Channels (Jin *et al.*, 2008; Kim *et al.*, 2012; Meng *et al.*, 2011). In this context, it was used by Atyabi *et al.* (2013) for dimensions reduction of both electrode and feature. Furthermore, Xu *et al.* (2014) considered simultaneously finding of the optimal frequency band and time interval of EEG signals using PSO. Finally, the adaptive noise canceller (ANC) was implemented with the PSO to detect hand movement based ERP from the EEGs by Ahirwal *et al.* (2014).

1.3 Problem Statement

Brain activities analysis from EEGs is indispensable in the study of epilepsy. An automatic computational model which is able to recognize epileptic EEGs is valuable for assisting the experts to analyze information of patients in the EEG recordings and for diagnosing and treatment epilepsy (Adeli *et al.*, 2003). Also, such methods form an integral part of closed-loop therapeutic systems that depend on implantable devices.

Automatic diagnosis of epilepsy is generally modeled as an abnormal EEGs recognition problem (Majumdar, 2011; Song and Zhang, 2013). As discussed in previous section, the AIS and PSO seem very promising fields for dealing with such problem. Therefore, these computational techniques have been considered to be widely studied in the area of EEG-based epileptic seizure recognition. Accordingly, the main question which must be answered is as follows:

How can the techniques of AIS and PSO produce different methods that perform efficiently and provide reliable recognition for epileptic activity in EEGs?

To study the main question of this research stated above, the following sub-research questions need to be addressed:

- *What are the abilities of individual algorithms of AIS and PSO in classifying EEGs?*

- *Can hybridization of AIS-based techniques with each other or with PSO improve the EEGs-based epileptic seizures recognition?*

- *Can modification of hybridization configuration enhance the performance of the proposed methods in recognizing epileptic EEGs?*

1.4 Objectives of Study

The main goal of this study is to investigate the capabilities of AIS and PSO in classifying EEGs to recognize the epileptic seizure in brain activities for purposes of epilepsy diagnosis. Therefore, the following specific objectives of the study have been stated:

1) To propose classification methods based on clonal selection and PSO for building nearest centroid classifier for EEGs.

2) To develop hybrid negative selection classification methods using the techniques of clonal selection and PSO for recognition of epileptic EEGs.

3) To further improve the efficiency of the hybrid methods proposed by configuring the hybridization on the basis of detection.

4) To evaluate the performance of the different proposed methods in diagnosing the epilepsy using EEG signals.

1.5 Scope of Study

This research studies the recognition of epileptic activity in human brain from EEGs by soft computing techniques. Hence, its scope limits to the following points.

1) The current work focuses on AIS and PSO to introduce hybrid and individual algorithms for automatic recognition of epileptic EEGs. In AIS, the theories of negative selection and clonal selection are studied.

2) In the preliminary stage, discrete wavelet transform (DWT) is applied for feature extraction of EEGs. The focus is on classification stage due to its importance in forming model discriminates between EEGs patterns.

3) The epilepsy diagnosis application using EEGs is considered in this study. Therefore, the publicly-available EEG data described in Andrzejak *et al.* (2001) is used to test the proposed methods. This dataset describes different cases for epilepsy diagnosis.

4) The performance of the proposed methods is evaluated using correct classification rate (CCR), true positive rate (TPR) or sensitivity, and true negative rate (TNR) or specificity which are the common measures in medical diagnosis tasks. Also, the algorithms are compared to one another and with other studies in literature.

1.6 Significance of Study

In this study, the abilities of the AIS and PSO techniques are widely explored in the field of EEG-based epileptic seizure recognition for diagnosis and treatment of epilepsy. More significantly, different methods are proposed which have not been introduced yet for classification of EEGs in order to test the individual and hybrid capabilities of AIS and PSO.

In this regard, the performance of clonal selection and PSO for classifying EEGs is studied individually through building NCC. Also, two hybrid negative selection models are developed in which clonal selection or PSO can be used to optimize the coverage of problem space. The first model is designed on the basis of classification where a set of detectors are produced for each class, while the second one takes into account the concept of detection and therefore the detectors are generated for only the abnormal class. The hybridization configuration and the solution structure of clonal selection (antibody) and PSO (particle) are different of each other for these two models.

Obviously, six algorithms are proposed in this research based on AIS and PSO for recognizing epileptic activities from EEGs: clonal selection classification algorithm (CSCA), particle swarm classification algorithm (PSCA), clonal negative selection classification algorithm (CNSCA), swarm negative selection classification algorithm (SNSCA), clonal negative selection detection algorithm (CNSDA), and swarm negative selection detection algorithm (SNSDA).

1.7 Thesis Organization

This thesis is organized into six major chapters and an introductory chapter. The second Chapter shows a review covering explanation of human brain activity and its recording techniques such as electroencephalogram (EEG). The EEG pattern recognition methodology and its applications in automated diagnosis of epilepsy are detailed in the chapter. Broad overviews on the fundamental methods which are used in this study are given. The use of these methods in EEG-based applications is also presented.

Chapter 3 describes the overall methodology followed to achieve the research objectives. It is introduced in a general operational framework that contains all phases and steps needed to be conducted in this work.

Chapter 4 presents an optimization based classification model to build nearest centroid classifier (NCC) for EEGs. The solution encoding and fitness function in this model are explained. The chapter describes in details two methods abstracted from the model by employing the clonal selection and particle swarm optimization (PSO) for optimization process. The experimental results of these algorithms are presented and their performances are discussed.

Chapter 5 introduces a classification model based on negative selection and optimization. The hybridization schema of the model to represent each class of the problem by a set of detectors is presented. The two versions of this model based on the use of clonal selection and PSO for optimization are developed and their performance for epileptic seizures recognition in EEGs is studied.

Chapter 6 illustrates an optimization based negative selection detection model for epilepsy diagnosis in EEGs. The chapter explains the schematic representation of the model and broadly discusses how a set of detectors is generated using negative selection algorithm (NSA) and optimized by clonal selection and PSO to recognize the epileptic activity in brain. At the end of the chapter, the results of all experiments conducted on different methods of this model are described accompanied with overall discussion.

Finally, Chapter 7 draws overall conclusions of the thesis, and highlights the contributions of this research. Recommendations and suggestions for possible future work are also discussed in the chapter.

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